

# Eigenvalues and eigenvectors

Let  $A \in \mathbb{R}^{n \times n}$ . If  $0 \neq v \in \mathbb{C}^n$  and  $\lambda \in \mathbb{C}$  satisfy

$$Av = \lambda v$$

then  $\lambda$  is called **eigenvalue**, and  $v$  is called **eigenvector**.

Given a matrix, we want to approximate its eigenvalues and eigenvectors.  
Some applications:

- Structural engineering (natural frequency, heartquakes )
- Electromagnetics (resonance cavity)
- Google's Pagerank algorithm
- ...

# The characteristic polynomial

The eigenvalues of a matrix are the roots of **the characteristic polynomial**

$$p(\lambda) := \det(\lambda I - A) = 0$$

However, computing the roots of a polynomial is a very ill-conditioned problem! We cannot use this approach to compute the eigenvalues.

# Eigenvalues and eigenvectors

Algorithms that compute the eigenvalues/eigenvectors of a matrix are divided into two categories:

- 1 Methods that compute all the eigenvalues/eigenvectors at once.
- 2 Methods that compute only a few (possibly one) eigenvalues/eigenvectors.

The methods are also different whether the matrix is symmetric or not. In this lesson we will discuss methods of type 2.

# Diagonalizable matrices

## Definition

We say that a matrix  $A \in \mathbb{C}^{n \times n}$  is diagonalizable if there exists a non singular matrix  $U$  and a diagonal matrix  $D$  such that  $U^{-1}AU = D$ .

The diagonal element of  $D$  are the eigenvalue of  $A$  and the column  $u_i$  of  $U$  is an eigenvector of  $A$  relative to the eigenvalue  $D_{i,i}$ .

Since a scalar multiple of an eigenvector is still an eigenvector, we can choose  $U$  such that  $\|u_i\|_2 = 1$  for  $i = 1, \dots, n$ .

Finally, we observe that if  $A$  is diagonalizable, since  $U$  is non singular, then the vectors  $\{u_1, \dots, u_n\}$  form a basis of  $\mathbb{C}^n$ .

From now on, we assume that the eigenvalues are numbered in decreasing order (in module), i.e.

$$|\lambda_1| \geq |\lambda_2| \geq \dots \geq |\lambda_n|$$

# Eigenvalues/eigenvectors of a symmetric matrix

## Theorem

All the eigenvalues of a real symmetric matrix are **real**. Moreover, there exists a basis of eigenvectors  $u_1, \dots, u_n$ , i.e.

$$Au_j = \lambda_j u_j$$

that are orthonormal, i.e.

$$(u_i, u_j) = \delta_{ij}$$

## The power method

We want to approximate the eigenvalue of  $A$  that is largest in module.

$v_0 =$  some vector with  $\|v_0\| = 1$ .

**for**  $k = 1, 2, \dots$

$$w = Av_{k-1}$$

$$v_k = w / \|w\|$$

$$\mu_k = (v_k)^H Av_k$$

apply  $A$   
normalize

Reyleigh quotient

**end**

### Theorem

Let  $A \in \mathbb{C}^{n \times n}$  be a diagonalizable matrix. Assume  $|\lambda_1| > |\lambda_2|$  and  $v_0 = \sum_{i=1}^n \alpha_i u_i$ , with  $\alpha_1 \neq 0$ . Then there exists  $C > 0$ , independent of  $k$ , such that

$$\|\tilde{v}_k - u_1\|_2 \leq C \left| \frac{\lambda_2}{\lambda_1} \right|^k,$$

$$\text{where } \tilde{v}_k = \frac{\|A^k v_0\|}{\alpha_1 \lambda_1^k} v_k.$$

## Proof

We expand  $v_0$  on the eigenvector basis  $\{u_1, \dots, u_n\}$  chosen s.t.  $\|u_i\| = 1$  for  $i = 1, \dots, n$ :

$$v_0 = \sum_{i=1}^n \alpha_i u_i, \quad \text{with } \alpha_1 \neq 0$$

It holds

$$A^k v_0 = \sum_{i=1}^n \alpha_i \lambda_i^k u_i \quad \text{and} \quad v_k = \frac{A^k v_0}{\|A^k v_0\|}$$

Hence, we can write

$$\tilde{v}_k = \frac{A^k v_0}{\alpha_1 \lambda_1^k} = u_1 + \sum_{i=2}^n \frac{\alpha_i}{\alpha_1} \left(\frac{\lambda_i}{\lambda_1}\right)^k u_i$$

At this point, it holds

$$\|\tilde{v}_k - u_1\|_2 = \left\| \sum_{i=2}^n \frac{\alpha_i}{\alpha_1} \left(\frac{\lambda_i}{\lambda_1}\right)^k u_i \right\|_2 \leq \sum_{i=2}^n \left\| \frac{\alpha_i}{\alpha_1} \left(\frac{\lambda_i}{\lambda_1}\right)^k u_i \right\|_2 = \sum_{i=2}^n \left| \frac{\alpha_i}{\alpha_1} \right| \left| \frac{\lambda_i}{\lambda_1} \right|^k$$

So, we obtain

$$\|\tilde{v}_k - u_1\|_2 \leq \sum_{i=2}^n \left| \frac{\alpha_i}{\alpha_1} \right| \left| \frac{\lambda_i}{\lambda_1} \right|^k \leq (n-1) \cdot \max_{i=2, \dots, n} \left( \left| \frac{\alpha_i}{\alpha_1} \right| \right) \left| \frac{\lambda_2}{\lambda_1} \right|^k = C \left| \frac{\lambda_2}{\lambda_1} \right|^k,$$

where we have defined  $C = (n-1) \cdot \max_{i=2, \dots, n} \left( \left| \frac{\alpha_i}{\alpha_1} \right| \right)$ . Since  $C$  does not depend on  $k$ , this concludes the proof.

The previous theorem implies that the sequence  $\{\tilde{v}_k\}$  converges to the eigenvector  $u_1$ . Since  $\tilde{v}_k$  is a scalar multiple of  $v_k$ , they have the same direction and this direction converges to the direction of  $u_1$ . As a result, for  $k$  that goes to  $+\infty$  the vector  $v_k$  tends to have the same direction of  $u_1$ . Thus  $v_k$  tends to be an eigenvector relative to  $\lambda_1$ .

### Remark

if  $|\lambda_2| \ll |\lambda_1|$  the convergence will be fast. On the other hand, if  $\lambda_2 \approx \lambda_1$  the convergence will be slow.